Identification and Reduction of spiky seismic traces using in-house developed module

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Keywords

Spiky traces, linear fitting, normal distribution, Z score value, python programming

Summary

In 2D-3C and 3D-3C seismic data acquisition with SVSM digital sensor (Multicomponent sensor), where channels were more than 2000, a long felt need was to identify all the spiky traces and relate it with the objects on the ground within the short span of time. Number of times it was difficult to identify the source of spiky traces as the channel numbers were large and they were spread over a large, usually 30 – 60 sq km. To overcome this problem, modules were developed in python programming language to segregate the spiky traces along with their SVSM sensor serial number, receiver and shot locations for identifying the SVSM.

The Spiky traces were plotted on google map to see the positioning of SVSM. The sensors falling in noise free areas were replaced with good sensors and those were tested in lab. Most of the times it was found that such SVSM were faulty.

Introduction

The digital sensor (SVSM) record spikes due to cultural, wind noise and shot generated noise. Cultural noises are due to villages, roads and underground oil and gas pipelines. The spiky SVSM subsequently settle over a period of time. Identifying the source of spiky traces whether it is due to SVSM sensor failure or due to objects on the ground in quick time is a challenging task due to large number of active channels and more than 100 shots per day.

The process of identifying the spiky traces in seismic recording and generating output based on SVSM serial number, receiver and shot locations was automated by developing a module in python programming language and subsequently added that tool to existing field processing software.

Method

In a shot gather, mean energy of the individual traces were calculated by squaring and summing up the amplitude values. It had been found that mean energy of the traces varies exponentially with respect to offset (Figure 1).

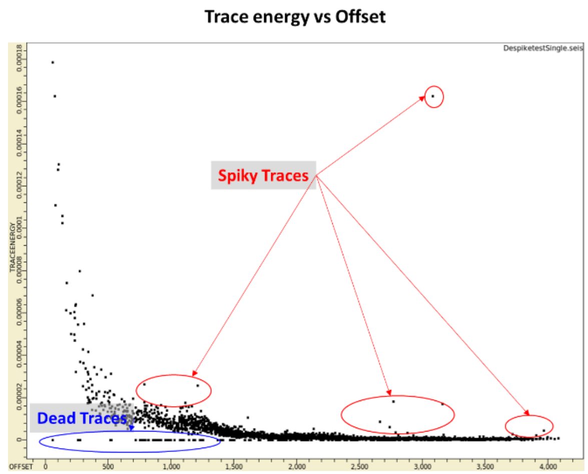

Figure 1: Trace energy vs Offset

The exponential relationship between the mean energy of the trace and offset can be obtained by linear fitting the logarithm of energy vs. logarithm of offsets. The traces violating the exponential relationship having high amplitudes could be classified as spiky traces and traces having very low amplitudes could be classified as dead traces.

The seismic traces violating the exponential relationship had to be identified. The error in curve fitting was calculated for every trace. Traces having large error compared to mean error can be classified as spiky or dead depending upon whether the error was above or below the mean. The errors of the traces and its mean in a shot gather will vary from shot to shot. The errors in curve fitting had to be standardized so that it will be more or less same value for the noisy traces in all shot gathers irrespective of the charge size and high amplitude noise due to logistics on the ground. To standardize errors, we assumed that errors were normally distributed and the Z scores were calculated. The Z score was number of standard deviations from the mean error of curve fitting i.e. Z score = [e-mean (e)]/std.dev (e) where e was the error. For example, Z score equals 1, means one standard deviation of error above mean error, and equals -1 means one standard deviation of error below mean error. In a normal distribution, approximately 68.3 % of the samples (traces here) falls between the +1 and -1 Z score, approximately 95.4 % of the samples (traces here) falls between the +2 and -2 Z score and approximately 99.1 % of the samples (traces here) falls between the +3 and -3 Z score. (Figure 2)

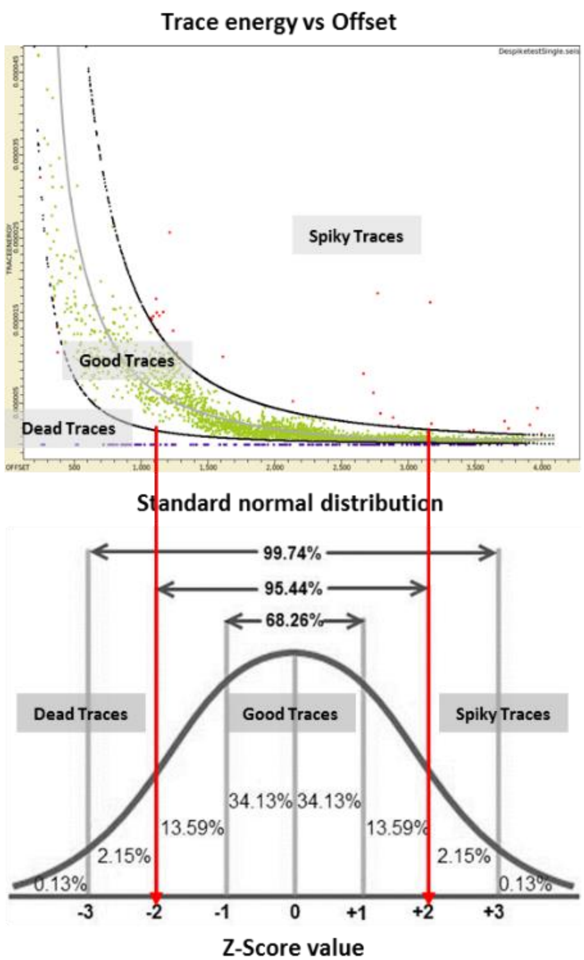

Figure 2: Trace classification using curve fitting

The spiky/dead traces were extreme cases in a shot gather. In a shot gather, the error of them deviates much away from the mean and having very high Z score (>3). Thus they fall on the both tail sides of the normal distribution curve. Those traces that fall in the middle of the normal distribution of the curve were good traces. (Figure 2).

In the module the user has to specify the absolute Z score above which the traces were considered to be noisy. This usually between 2 and 3 depends upon the field conditions and user judgment.

The zero Z score corresponds to the mean error. In case of curve fitting, the mean error would be zero and it corresponds to best fit curve shown in grey color in Figure 2. For positive Z score (above mean error) and negative Z score (below mean error) the two curves were drawn (black curves in Figure 2). The traces falling in between these curves were classified as good traces, which fall above the top curve were spiky and which fall below the bottom curve were dead.

Once the spiky traces were classified the next step was to ascertain that whether it's due to element failure or due to cultural/shot generated noise in the field. So that necessary actions can be taken in the field. For this purpose, various reports were generated such as number of spiky traces in a particular shot, number of traces recorded at a particular receiver location out of that what percentage of traces were spiky and also number of traces recorded by a particular SVSM sensor in a specific period, out of that what percentage of traces are spiky. These reports were helpful in deciphering the possible causes of the spiky traces. For example, if a particular receiver location records high percentage of spiky traces that means that the problem can be due to the location of the receiver near to logistics such as urban villages, roads, tube well motors, nearby shot blast etc. High percentage of spiky traces was recorded if receivers were near passage of heavy vehicles or railway trains. Radio station broadcasting also cause spiky traces.

The algorithms were written in python programming language. They were added as a two new modules to existing Field Processing software OpenCPS. One for classifying the traces and other for generating reports.

Those users who are familiar with OpenCPS can easily use these modules and generate results as they could in any other OpenCPS modules.

Limitation

This algorithm assumes that noisy traces have anomalous energies which was either very high or very low compared to the mean. But if the noisy/spiky traces have same energy range level of the regular signal that could not be discriminated.

Examples

The developed module had been tested on seismic data of GP-81 and the various outputs are discussed here.

The segregation of spiky & good traces and their difference is shown in Figure 3.

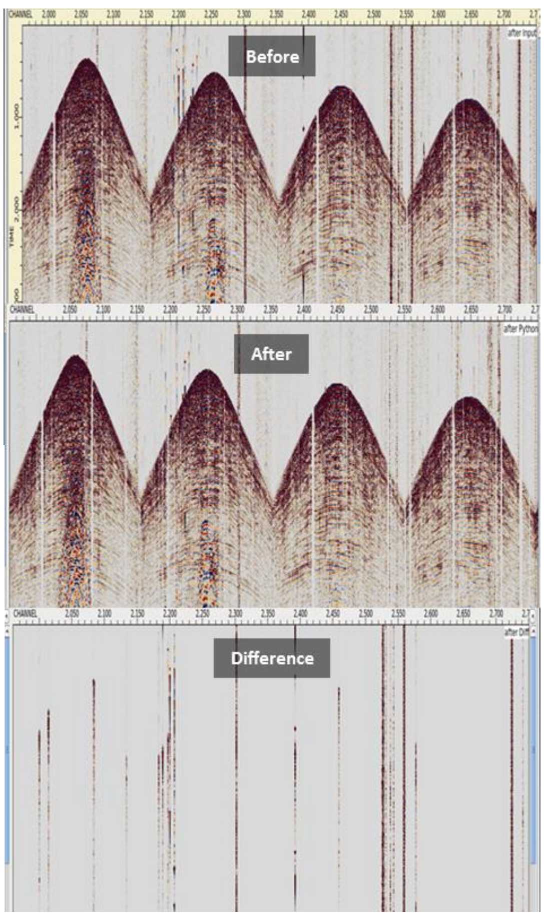

Figure 3. Before, after and difference in sample seismic section after applying the module

a) Day wise analysis

The output of module based on SVSM sensor on daily basis would give the list of SVSM serial numbers along with number of good and spiky traces recorded by corresponding SVSM sensors. The screenshot of the sample output generated by the module as shown in Figure 4. The output data plotted on the Google map (Figure 5) shows the SVSM location along with their serial numbers. The color indicates the number of spiky traces it recorded in that day. Those SVSM sensors recorded spiky traces even at logistics free locations were segregated and lab tested before deploying again in field.

SVSM_Serial	REC_X	REC_Y	SpikyRecordingCount	DeadRecordingCount	GoodRecordingCount
4766	10000	20000	9	0	117
7701	10001	20001	0	0	126
10206	10002	20002	4	0	59
10752	10003	20003	0	0	126
13179	10004	20004	3	0	92
13336	10005	20005	0	0	31
14054	10006	20006	1	0	125
14302	10007	20007	2	0	124
14684	10008	20008	6	0	120
15248	10009	20009	6	0	120
15417	10010	20010	0	0	126
15618	10011	20011	34	0	92

Figure 4. Sample report of Spiky traces in a day

Figure 5. Spiky traces along with SVSM sensor serial number

b) Swath wise analysis

The test was run on a single swath comprising 1629 shots. This was a post operation analysis after acquiring data in a swath. The output plotted on Google map. The color indicates the number of spiky traces it recorded. It was observed that the number of spiky traces recorded close to the villages, roads and canals are high. The traffic on by lanes and running of motors also increase the spiky traces (Figure 6). The spiky traces in noise free area were taken out, and after testing these SVSM were found bad.

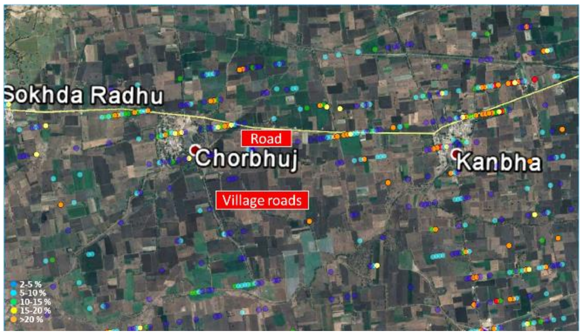

Figure 6. Spiky traces percentage at various receiver locations

Conclusions

The modules developed in-house had segregated the spiky traces and generated output such as number of spiky traces recorded by a particular SVSM sensor, at a particular receiver and shot locations. The SVSM co-ordinates were plotted on Google map and oil/gas pipe line maps.

The information available on these maps helps field geophysicist in identifying the causes of spiky traces. The SVSM sensors having spiky traces in noise free places were replaced with good SVSM, thereby reducing spiky traces.

The loading of data and running of modules in FPU takes half an hour time. The same task done manually on daily basis is a tedious and time consuming task.

The modules were added to the existing field processing software OpenCPS so that the tool can be used in the same way as other tools in the FPU without any additional efforts.

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Views expressed in this paper are that of the authors only and may not necessarily be of ONGC.

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